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Better Late than Never: A Multilayer Network Model Using Metaplasticity for Emotion Regulation Strategies

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Abstract. Adaptivity in emotion regulation strategies has always been considered as one of the key factors for health. As the choices of emotion regulation strategies change as per context, the priorities of strategies also change with time. This phenomenon is called plasticity. This paper focuses on network-oriented modeling of the concept of metaplasticity from recent neurological literature which controls the plasticity. Simulation results are presented for the elaboration of the concept in choice of emotion regulation strategies with age.

Keywords: Plasticity · Metaplasticity · Emotion regulation · Gender · Reappraisal · Expressive suppression

1 Introduction

In the choice of emotion regulation strategies, flexibility per context is a well-established fact now in cognitive and social sciences [1]. Research considering the changes in emotion regulation strategies with time can be found, for example, in [2]. A factor "changes with time" can be described by changes in emotion regulation strategies with age [3]. A vast body of literature is available showing that changes in the choice of emotion regulation strategies, caused by various factors, take place as a person grows [4]; this is also highlighted by socioemotional selectivity theory (SST) [2]. These changes are referred to as *plasticity* in the literature from the neurocognitive sciences.

Recently, an increasing amount of work has been reported about *metaplasticity* [5, 6] or plasticity of plasticity. For emotion regulation, these concepts apply to the adaptive changes that take place in the choice of emotion regulation strategies over time with age.

This paper extends the work presented in [7] which focuses on age and gender differences in choice of emotion regulation strategies. When we say "gender" we refer to the unary biological as well as social role, i.e., male vs female throughout the paper. In this paper the concepts of plasticity and metaplasticity [5, 6] have been applied for age differences in choice of emotion regulation strategies by using the modeling approach for multi-layered adaptive networks and its supporting software environment described in [8–10]. Complexity of the emerging behaviour addressed in this paper lies in the multiple orders of adaptivity, and the dynamic and adaptive interaction between the layers of the obtained network.

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Plasticity of plasticity in emotion regulation is a novice concept in the field of AI and network-oriented modeling. In the multi-layered network-oriented modeling approach used from [9, 10], a base network model is extended by on top of it adding two layers, respectively, for first-order adaptation of (some of) the base network connections, and for second-order adaptation by control of the first-order adaptation speed and intensity of the changes that take place over time. Simulation results are reported to illustrate the network behaviour emerging from the interaction (or co-evolution) between the three layers (base network dynamics and first- and second-order adaptation dynamics). In rest of the paper, Sect. 2 presents a theoretical background for the model. Section 3 presents the multilayer network model, Sect. 4 presents simulation experiments of the model. Finally, Sect. 5 concludes the paper.

2 Background

Shift in choice of emotion regulation strategies occurs as a person grows and it involves many factors that influence this shift from one strategy to another strategy. According to SST [2], this shift is because of the time constraint being experienced by older adults which alters their motivational goals. Similarly, [11] states that younger and older adults use different kinds of emotion regulation strategies and age-specific developmental increase and decrease takes place in the use of emotion regulation strategies. Moreover, According to SST [2] older adults turn to more use of antecedent-focused strategies like reappraisal from response-focused strategies like suppression. In line with these findings, [12] found an increased use of reappraisal and decrease use of suppression with age (from 20 to 60). A reason for this shift from response-focused strategies to antecedent-focused strategies may be found in the "strength and vulnerability integration theory" [13] stating that as physiological flexibility decreases with age, it becomes difficult to implement response-focused strategies. Therefore, older adults may use more antecedent-focused strategies.

Similarly, [14] state that older people are "more likely" to reappraise than younger adults. In terms of control in emotional situations, older people are better in controlling their emotions [15, 16] and quicker in returning to a positive mood after a negative mood [17, 18] in comparison to younger adults. Confirming these findings, [19, 20], not only cognitive reappraisal is considered to be efficient in downregulating negative emotional experiences, it also helps in decreasing the psychological distress, which is reversed to suppression. In case of suppression, distress still remains high even if the expression of emotion is suppressed successfully [21]. In line with this discussion, [22] suggest that being an effective emotion regulation strategy, it is cognitive reappraisal that helps older people in retaining a positive emotional state. In contrast, younger adults prefer confrontational coping, as reported by [23]. The reason of an increased use of reappraisal can also be because older adults need fewer cognitive resources [24] as compared to their younger counterparts to down-regulate negative emotional response. Increased use of reappraisal and decreased use of suppression is also supported by series of findings like [25] reporting that emotional wellbeing improves with age from adulthood to early old age, and [26] reporting that use of reappraisal helps in emotional wellbeing when compared to expressive suppression. This supports the idea that decrease in negative affect and increase in positive affect occurs due to the increase in the use of reappraisal as an emotion regulation strategy with increasing age [3].

So, the more general concept of plasticity also applies to the experience of emotions. Also, in other literature this is indicated. For instance, [27, 28] put forward that the intensity of negative emotions decreases with age while the intensity of positive emotions either remains stable or increases with age. Moreover, older people tend to consider a stressful situation less threatening [29] in comparison to younger adults and give weaker negative reaction [30, 31]. Studies like [32] also found decreased rate of depression/anxiety in older people in comparison to younger adults. Similarly, [33] also support the notion that frequency of negative affect decreases with age while positive affect remains stable. Various individual differences can be found in self-regulation in adults [34]. However, overall, findings suggest that some development takes place in emotional experience and regulatory capabilities into the second half of life. At the same time, studies like [35] also found decline in cognitive resources with age that too is subjected to individual differences.

The concept of plasticity in emotion regulation strategies has long ago been defined by [36] stating that maturity in cognition is bound to improvements in cognitive reappraisal and older people exhibit more of this cognitive maturity than their younger counterparts [37]. Similarly, [38, 39] state that flexibility in goal adjustment increases with age. These findings provide a strong base for the network model introduced here.

3 The Multilayered Network Model

This section describes the computational model presented in this paper as well as the Network-Oriented Modeling approach for adaptive networks based on network reification [8–10] that has been employed for designing the network model, and performing simulations with it.

The multi-layered network model presented in Fig. 1. demonstrates the phenomena of plasticity and metaplasticity. Table 1 provides overview of the various states of the model. The first (bottom) layer describes the base level, which shows the basic processes of the two strategies, i.e., expressive suppression and cognitive reappraisal. Expressive suppression suppresses the expression of the emotion while sensory representation and the negative belief about the stimulus still remain high. In contrast, reappraisal changes the beliefs about the stimulus which, as a result, decreases the intensity of the negative emotion while increasing positive emotions about the stimulus.

The second layer describes first-order network adaptation at the first reification level, which demonstrates the Hebbian learning process taking place throughout one's life in various forms. Here, the person learns about which emotion regulation strategy to use over time. This happens by changing the **W** states that provide reified representations for the connection weights used at the base level. Initially, the person is using expressive suppression in younger ages. The use of reappraisal increases with the increase in age, which discourages the use of expressive suppression at the base level.

Table 1. Overview of the states of the multi-layered network model in Fig. 1.

State		Explanation	Level
X_1	ws_s	World state for stimulus s	Base level
X_2	ss_s	Sensor state for stimulus s	
X_3	srs_s	Sensory representation state for stimulus s	
X_4	ps_a	Preparation state for action a	
X_5	es_a	Execution state for action a	
X_6	ss_b	Sensor state for body state b	
X_7	srs_b	Sensory representation state for body sate b	
X_8	fs_b	Feeling state for body state b	
X_9	ps_b	Preparation state for body state b	
X_{10}	es_b	Expression execution state for body state b	
X_{11}	bs_-	Belief state for negative belief −	
X_{12}	bs_+	Belief state for positive belief +	
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	Control state for reappraisal	
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	Control state for suppression	
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	Monitoring state for distress	
X_{16}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	Reified representation state for connection weight $\boldsymbol{\omega}_{\mathrm{fs}b,\mathrm{csreapp}}$	First reification level
X_{17}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	Reified representation state for connection weight $\boldsymbol{\omega}_{\mathrm{fs}b,\mathrm{cssup}}$	
X_{18}	$\mathbf{M}_{\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}}$	Reified representation state for speed factor $\boldsymbol{\eta}$ for $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	Second reification level
X_{19}	$\mathbf{H}_{\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}}$	Reified representation state for persistence factor $\boldsymbol{\mu}$ for $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	
X_{20}	$\mathbf{H}_{\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}}$	Reified representation state for speed factor $\boldsymbol{\eta}$ for $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	
X_{21}	$\mathbf{M}_{\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}}$	Reified representation state for persistence factor $\boldsymbol{\mu}$ for $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	

The third layer describes second-order adaptation at the second reification level, which controls the speed as well as persistence factor of the first-order learning phenomena at the first reification level. It uses **H** states and **M** states as reified representations. The **H** states control the adaptation speed factors for the first-order adaptation, modeled by their respective **W** states, and the **M** states control the persistence level of the first-order adaptation, modeled by their respective **W** states.

Hebbian learning can take place for connections between any two states at the base level. For instance, the connection from fs_b to $\mathrm{cs}_{\mathrm{reapp}}$ in the base model is adaptive but the connection weight is no state of the base level. Instead, this weight is represented by state $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$ at the first reification level. As learning itself is subjected to change too, its change in adaptation speed and persistence is controlled by states at the 2[nd] reification level. For instance, the speed and persistence of $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$ (first reification level state) are controlled by the second reification level states $\mathbf{H}_{\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}}$ and $\mathbf{M}_{\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}}$

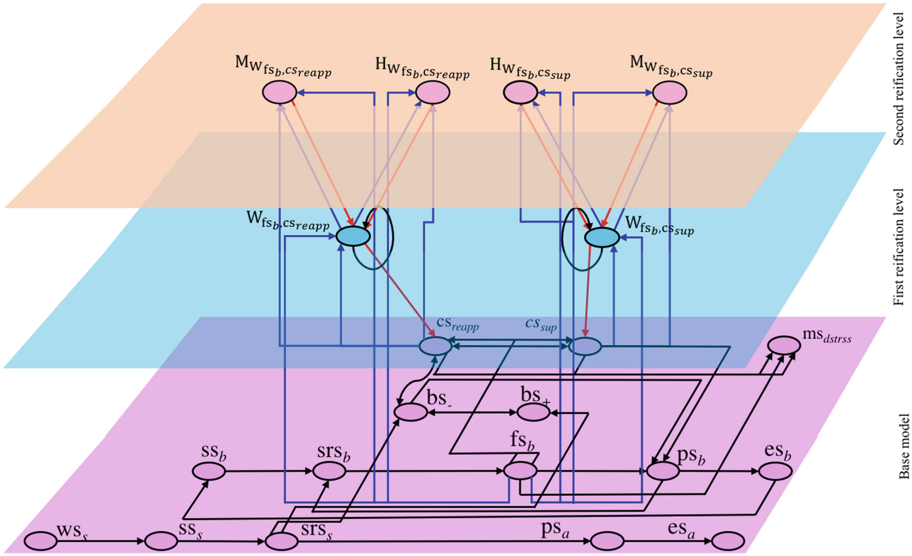

Fig. 1. Multi-layered adaptive network model for emotion regulation strategies with age.

representing this adaptation speed and persistence, respectively. Similarly, there is possibility of many other layers on top of this.

The full specification of the multi-layered network model by role matrices can be found in Box 1 and Box 2. Each matrix addresses some network characteristic and has rows according to all states X_j with in that row the data for that characteristic. Here **mb** specified the states with incoming connections to state X_j. In general, the green cells with values indicate the static (non-adaptive) network characteristics, and the red cells with names X_i indicate adaptive characteristics where the value of X_i plays the role of that characteristic. As an example, in the connectivity role matrix **mcw** for connection weights, for the control states X_{13} and X_{14} (cs_{reapp} and cs_{sup}) at the base level it is indicated in the first column that the connection from the first base state X_8 (the feeling state fs_b) indicated in the first column in **mb** is adaptive and is represented by X_{16} resp. X_{17} ($\mathbf{W}_{fs_b, cs_{reapp}}$ resp. $\mathbf{W}_{fs_b, cs_{sup}}$).

The role matrices can be used as input for the modeling environment described in [9] and can be executed then. It represents the conceptual representation of the model and shows how each node is influenced by other nodes in the network. Starting from base network model to the second reification level, Box 1 and 2 specify these influences. For more background on the role matrices specification format used here, and the modeling environment, see [9, 10].

mb connectivity: base connectivity		1	2	3
X_1	ws_s	X_1		
X_2	ss_s	X_1		
X_3	srs_s	X_2		
X_4	ps_a	X_3		
X_5	es_a	X_4		
X_6	ss_b	X_{10}		
X_7	srs_b	X_9	X_6	
X_8	fs_b	X_7		
X_9	ps_b	X_8	X_{11}	X_{14}
X_{10}	es_b	X_9		
X_{11}	bs_-	X_3	X_{13}	X_{12}
X_{12}	bs_+	X_3	X_{11}	
X_{13}	cs_{reapp}	X_8	X_{11}	
X_{14}	cs_{sup}	X_8	X_{13}	
X_{15}	ms_{dstrss}	X_8	X_{13}	X_{14}
X_{16}	$\mathbf{W}_{fs_b,cs_{reapp}}$	X_8	X_{13}	X_{16}
X_{17}	$\mathbf{W}_{fs_b,cs_{sup}}$	X_8	X_{14}	X_{17}
X_{18}	$\mathbf{MW}_{fs_b,cs_{reapp}}$	X_8	X_{13}	X_{16}
X_{19}	$\mathbf{HW}_{fs_b,cs_{reapp}}$	X_8	X_{13}	X_{16}
X_{20}	$\mathbf{HW}_{fs_b,cs_{sup}}$	X_8	X_{14}	X_{17}
X_{21}	$\mathbf{MW}_{fs_b,cs_{sup}}$	X_8	X_{14}	X_{17}

mcw connectivity: connection weights		1	2	3
X_1	ws_s	1		
X_2	ss_s	1		
X_3	srs_s	1		
X_4	ps_a	0.1		
X_5	es_a	0.2		
X_6	ss_b	1		
X_7	srs_b	0.5	0.15	
X_8	fs_b	1		
X_9	ps_b	0.4	0.5	-0.9
X_{10}	es_b	1		
X_{11}	bs_-	0.6	-0.7	-0.4
X_{12}	bs_+	0.4	-0.4	
X_{13}	cs_{reapp}	X_{16}	0.2	
X_{14}	cs_{sup}	X_{17}	-1	
X_{15}	ms_{dstrss}	0.4	-0.4	0.4
X_{16}	$\mathbf{W}_{fs_b,cs_{reapp}}$	1	1	1
X_{17}	$\mathbf{W}_{fs_b,cs_{sup}}$	1	1	1
X_{18}	$\mathbf{MW}_{fs_b,cs_{reapp}}$	1	1	1
X_{19}	$\mathbf{HW}_{fs_b,cs_{reapp}}$	1	1	1
X_{20}	$\mathbf{HW}_{fs_b,cs_{sup}}$	0.6	0.8	0.8
X_{21}	$\mathbf{MW}_{fs_b,cs_{sup}}$	0.6	0.8	0.5

Box 1 Role matrices for connectivity

In Box 1, matrix **mb** represents for any node of the network its incoming connections. These connections in **mb** are either between states at the same level or from lower level to higher level, i.e. no downward connection from a higher to a lower level, as the downward connections are the connections which effectuate adaptivity and are specified in the other role matrices. To the right, in matrix **mcw** the values between 0–1 represent connection weights of the incoming connections while the X_i represent the respective states in the higher level that represent and control the (incoming) adaptive connection to that specific state.

In Box 2 below, it can be seen that the Hebbian learning states in first reification level has downward incoming connections from the second reification level one each for speed factor and for persistence.

mcfw aggregation: combination function weights		1 alogistic	2 hebb	3 id
X_1	ws_s			1
X_2	ss_s			1
X_3	srs_s			1
X_4	ps_a			1
X_5	es_a			1
X_6	ss_b			1
X_7	srs_b	1		
X_8	fs_b			1
X_9	ps_b	1		
X_{10}	es_b			1
X_{11}	bs_-	1		
X_{12}	bs_+	1		
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	1		
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	1		
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	1		
X_{16}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$		1	
X_{17}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$		1	
X_{18}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	1		
X_{19}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	1		
X_{20}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	1		
X_{21}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	1		

mcfp aggregation: combination function parameters		1 alogistic σ	τ	2 hebb μ	3 id
X_1	ws_s				
X_2	ss_s				
X_3	srs_s				
X_4	ps_a				
X_5	es_a				
X_6	ss_b				
X_7	srs_b	10	0.3		
X_8	fs_b				
X_9	ps_b	10	0.3		
X_{10}	es_b				
X_{11}	bs_-	8	0.2		
X_{12}	bs_+	8	0.2		
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	5	0.8		
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	12	0.2		
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	8	0.5		
X_{16}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$			X_{18}	
X_{17}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$			X_{19}	
X_{18}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	12	0.2		
X_{19}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	4	0.2		
X_{20}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	10	0.3		
X_{21}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	10	0.3		

ms timing: speed factors		1
X_1	ws_s	0
X_2	ss_s	1
X_3	srs_s	1
X_4	ps_a	1
X_5	es_a	1
X_6	ss_b	1
X_7	srs_b	1
X_8	fs_b	1
X_9	ps_b	1
X_{10}	es_b	1
X_{11}	bs_-	1
X_{12}	bs_+	1
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	0.1
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	0.4
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	0.5
X_{16}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	X_{19}
X_{17}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	X_{20}
X_{18}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	0.3
X_{19}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	0.3
X_{20}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	0.3
X_{21}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	1

Box 2 Role matrices for aggregation and timing

4 Simulation Results

The scenarios addressed in this work are inspired by [7] where both age and gender have been considered for the difference in choice of emotion regulation strategies. The extended multi-layered network model introduced here only considers age for the choice in emotion regulation strategies. Novelty of the model is that it is a multi-layered adaptive network model with dynamic states which change in an adaptive manner with Hebbian learning. The Hebbian learning itself is controlled in an adaptive manner as well, as in real life. Table 2 provides the initial values of the states of the model.

Table 2. Initial values of the states

State	ws_s	All other base states	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	$\mathbf{H}_{\mathbf{W}\,\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	$\mathbf{H}_{\mathbf{W}\,\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	$\mathbf{H}_{\mathbf{W}\,\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	$\mathbf{M}_{\mathbf{W}\,\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$
Initial value	1	0	0.3	0.3	0.5	0.5	0.9	0.9

Figure 2 shows the speed factor and persistence factor reification states of the two reified **W** states given in Fig. 3. It can be seen in the graph that both the factors are initially increasing for both the reified states but after some time $\mathbf{H}_{\mathbf{W}\,\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$ and

$\mathbf{M}_{\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}}$ get decreasing. This phenomenon demonstrates metaplasticity wherein the learning itself is dynamic, i.e. increases/decreases with time. This makes the person either stick to previous emotion regulation strategies or switch from one strategy to another strategy after learning takes place over the years.

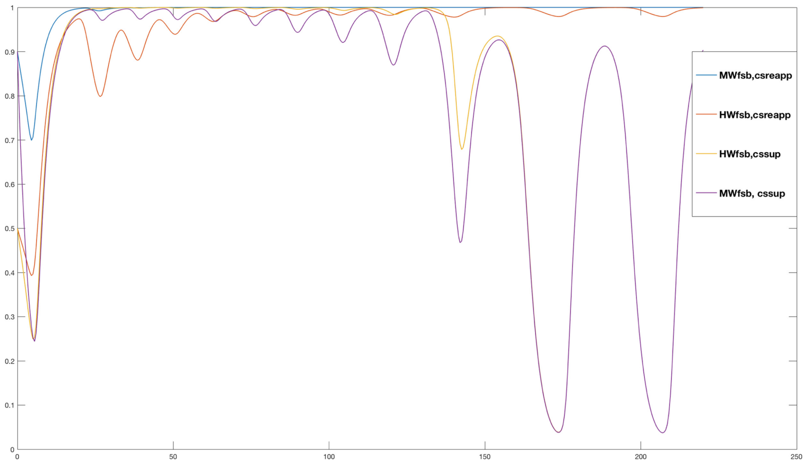

Fig. 2. Second-order reified representation states for speed and persistence factors.

In Fig. 3 the reified states are given, where $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$ increases slowly and gradually while $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$ decreases slowly and gradually until it gets equal to zero. Initially, younger adults use suppression; therefore, $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$ is high. On the other hand $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{csreapp}}}$ is, though, low but increasing slowly with increase in age. Finally, $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{csreapp}}}$ is high enough to activate $\mathrm{cs}_{\mathrm{reapp}}$ instead of $\mathrm{cs}_{\mathrm{sup}}$. This demonstrates the learning that takes place over the years and changes priorities over time.

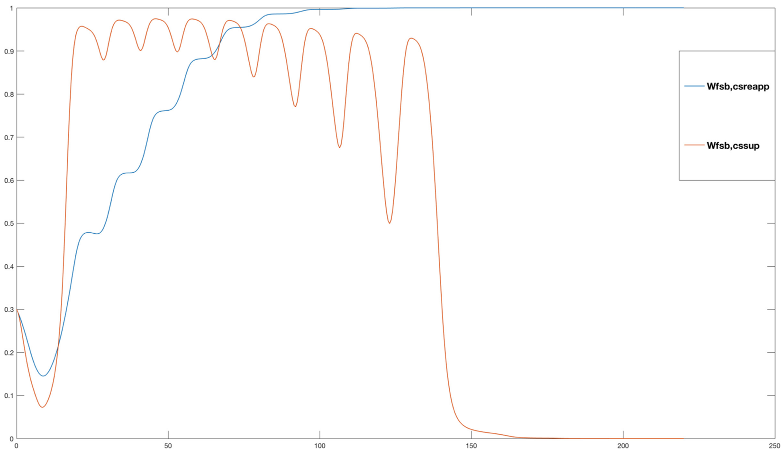

Fig. 3. First-order reified representation state over time (Age).

Figure 4 demonstrates the entire scenario in which choice of emotion regulation strategies changes as a person grows. Initially, suppression gets activated (in young age) and suppresses the body states by not letting the person to express his or her emotions while the negative belief and intensity of the stimulus stay high during this whole process. In the later stages of life, the person switches from suppression to reappraisal. It can be seen that this shift between strategies doesn't not take place at once. Tendency towards reappraisal is increasing over time and finally it becomes the major emotion regulation strategy. Effective states of this graph can be further studied in detail in Fig. 5.

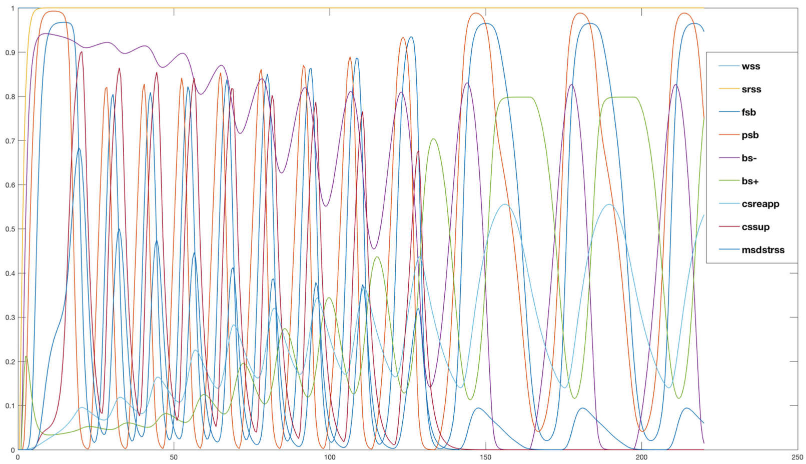

Fig. 4. Switching from suppression to reappraisal over time.

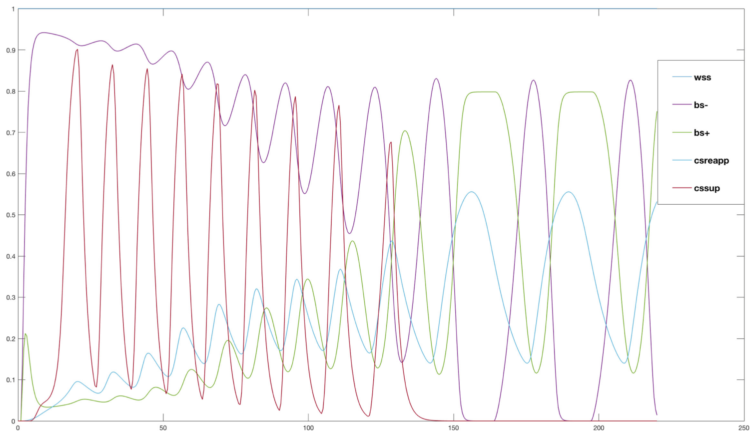

Fig. 5. Demonstration of the effective states over time.

Figure 5 shows only the effective states of Fig. 4. Initially, as suppression gets activated, it can be seen that bs- still remains high and bs+ remains low. This shows suppression of expression while the intensity of emotions still remains the same. At the same time, due to Hebbian learning, activation of reappraisal is continuously decreasing while suppression is increasing when, finally, activation of reappraisal is low enough to make reappraisal effectively get activated and change belief of the person. Therein, it can be seen the bs- decreases while bs_+ increases. This demonstrates the phenomenon of metaplasticity exactly as described by literature from cognitive neuroscience.

5 Conclusion

Change in the choice of emotion regulation strategies, over time, is a proven fact in social and psychological literature so far. This paper brings this phenomenon into the field of network modeling within computer science and artificial intelligence. The layered approach used in this paper makes the phenomenon very dynamic and adaptive which is exactly as it takes place in real life. First, it establishes the fact that all such phenomena are prone to changes, second, the speed and intensity of this change in choice itself is changing over time.

Moreover, the layered network modeling approach used for this network model also takes the application of network-oriented modeling a step forward. This layered and abstract approach makes it possible to model every real-life phenomenon in a real but relatively easy way. The complexity of the network model lies in the dynamics of the different layers (with various adaptive parameters like speed factors for strategy choice adaptation over time, and persistency of learning), and the interaction or co-evolution of these layers. No other network models that address these second-order adaptive emotion regulation processes are known to the authors.

References

1. Aldao, A., Sheppes, G., Gross, J.J.: Emotion regulation flexibility. Cogn. Ther. Res. **39**(3), 263–278 (2015)
2. Carstensen, L.L., Isaacowitz, D.M., Charles, S.T.: Taking time seriously: a theory of socioemotional selectivity. Am. Psychol. **54**(3), 165–181 (1999)
3. Nakagawa, T., Gondo, Y., Ishioka, Y., Masui, Y.: Age, emotion regulation, and affect in adulthood: the mediating role of cognitive reappraisal. Jpn. Psychol. Res. **59**(4), 301–308 (2017)
4. Allen, V.C., Windsor, T.D.: Age differences in the use of emotion regulation strategies derived from the process model of emotion regulation: a systematic review. Aging Ment. Health **23**(1), 1–14 (2019)
5. Abraham, W.C., Bear, M.F.: Metaplasticity: the plasticity of synaptic plasticity. Trends Neurosci. **19**(4), 126–130 (1996)
6. Abraham, W.C.: Metaplasticity: tuning synapses and networks for plasticity. Nat. Rev. Neurosci. **9**(5), 387–399 (2008)

7. Zhenyu, G., Liu, R., Ullah, N.: A temporal-causal network model for age and gender difference in choice of emotion regulation strategies. In: Nguyen, N.T., et al. (eds.). LNAI 11683, pp. 106–117. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-28377-3_9
8. Treur, J.: Multilevel network reification: representing higher order adaptivity in a network. In: Proceedings of ComplexNetworks 2018, vol. 1. Studies in Computational Intelligence, vol. 812, pp. 635–651. Springer (2018)
9. Treur, J.: Modeling higher-order adaptivity of a network by multilevel network reification. Netw. Sci. (2019, in press)
10. Treur, J.: Network-oriented modeling for adaptive networks: designing higher-order adaptive biological, mental and social network models. Springer (2020, to appear). https://www.researchgate.net/publication/334576216
11. Zimmermann, P., Alexandra, I.: Emotion regulation from early adolescence to emerging adulthood and middle adulthood: age differences, gender differences, and emotion-specific developmental variations. Int. J. Behav. Dev. **38**(2), 182–194 (2014)
12. John, O., Gross, J.J.: Healthy and unhealthy emotion regulation: personality processes. Individ. J. Pers. **72**(6), 1301–1334 (2004)
13. Charles, S.T.: Strength and vulnerability integration: a model of emotional well-being across adulthood. Psychol. Bull. **136**(6), 1068–1091 (2010)
14. Charles, S.T., Laura, L.C.: Emotion regulation and aging. In: Gross, J.J. (ed.) Handbook of Emotion Regulation, pp. 307–327. The Guildford Press, New York (2007)
15. Lawton, M.P., Kleban, M.H., Rajagopal, D., Jennifer, D.: Dimensions of affective experience in three age groups. Psychol. Aging **7**(2), 171–184 (1992)
16. Phillips, L.H., Henry, J.D., Hosie, J.A., Milne, A.B.: Age, anger regulation and well-being. Aging Ment. Health **10**(3), 250–256 (2006)
17. Carstensen, L.L., Pasupathi, M., Mayr, U., Nesselroade, J.R.: Emotional experience in everyday life across the adult life span. J. Pers. Soc. Psychol. **79**(4), 644–655 (2000)
18. Larcom, M.J., Derek, M.I.: Rapid emotion regulation after mood induction: age and individual differences. J. Gerontol. Ser. B Psychol. Sci. Soc. Sci. **64**(6), 733–741 (2009)
19. Silje, H., Kraft, P., Corby, E.: Emotion regulation: antecedents and well-being outcomes of cognitive reappraisal and expressive suppression in cross-cultural samples. J. Happiness Stud.: Interdiscip. Forum Subj. Well-Being **10**(3), 271–291 (2009)
20. Oliver, P.J., Gross, J.J.: Healthy and unhealthy emotion regulation: personality processes, individual differences, and life span development. J. Pers. **72**(6), 1301–1333 (2004)
21. Gross, J.J., et al.: Emotion and aging: experience, expression, and control. Psychol. Aging **12**(4), 590–599 (1997)
22. Dannii, Y.Y., Wong, C.K.M., Lok, D.P.P.: Emotion regulation mediates age differences in emotions. Aging Ment. Health **15**(3), 414–418 (2011)
23. Folkman, S., Lazarus, R.S., Pimley, S., Novacek, J.: Age differences in stress and coping processes. Psychol. Aging **2**(2), 171–184 (1987)
24. Scheibe, S., Blanchard-Fields, F.: Effects of regulating emotions on cognitive performance: what is costly for young adults is not so costly for older adults. Psychol. Aging **24**(1), 217–223 (2009)
25. Scheibe, S., Carstensen, L.L.: Emotional aging: recent findings and future trends. J. Gerontol. Ser. B Psychol. Sci. Soc. Sci. **65B**(2), 135–144 (2010)
26. Debora, C.: Cognitive reappraisal and expressive suppression strategies role in the emotion regulation: an overview on their modulatory effects and neural correlates. Front. Syst. Neurosci. **8**, 1–6 (2014)
27. Christina, R., Li, S., Smith, S.: Intraindividual variability in positive and negative affect over 45 days: do older adults fluctuate less than young adults? Psychol. Aging **24**(4), 863–878 (2009)

28. Mroczek, D.K., Kolarz, C.M.: The effect of age on positive and negative affect: a developmental perspective on happiness. J. Pers. Soc. Psychol. **75**(5), 1333–1349 (1998)
29. Charles, S.T., Almeida, D.: Daily reports of symptoms and negative affect: not all symptoms are the same. Psychol. Health **21**(1), 1–17 (2006)
30. Kira, S.B., Fingerman, K.L., Almeida, D.M.: Age differences in exposure and reactions to interpersonal tensions: a daily diary study. Psychol. Health **20**(2), 330–340 (2005)
31. Kira, S.B., Fingerman, K.L.: Age and gender differences in adults' descriptions of emotional reactions to interpersonal problems. J. Gerontol. Ser. B Psychol. Sci. Soc. Sci. **58**(4), 237–245 (2003)
32. Regier, D.A., et al.: One-Month prevalence of mental disorders in the United States: based on five epidemiologic catchment area sites. Arch. Gen. Psychiatry **45**(11), 977–986 (1988)
33. Charles, S.T., Reynolds, C.A., Gatz, C.A.: Age-related differences and change in positive and negative affect over 23 years. J. Pers. Soc. Psychol. **80**(1), 136–151 (2001)
34. Rothbart, M.K., Ahadi, S.A., Evans, D.E.: Temperament and personality: origins and outcomes. J. Pers. Soc. Psychol. **78**(1), 122–135 (2000)
35. Verhaeghen, P.: Aging and executive control: reports of a demise greatly exaggerated. Curr. Dir. Psychol. Sci. **20**(3), 174–180 (2011)
36. Labouvie-Vief, G., DeVoe, M., Bulka, D.: Speaking about feelings: conceptions of emotion across the life span. Psychol. Aging **4**(4), 425–437 (1989)
37. Labouvie-Vief, G., Blanchard-Fields, F.: Cognitive ageing and psychological growth. Ageing Soc. **2**(2), 183–209 (1982)
38. Heckhausen, J., Schulz, R.: A life-span theory of control. Psychol. Rev. **102**(2), 284–304 (1995)
39. Brandtstädter, J., Renner, G.: Tenacious goal pursuit and flexible goal adjustment: explication and age-related analysis of assimilative and accommodative strategies of coping. Psychol. Rev. **5**(1), 58–67 (1990)